Linear SVM for Underwater Magnetic Signals Based Port Protection

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Abstract**:** The classical approach used to solve the underwater port protection problem is the acoustic based technique (sonar sensors). It has been shown that integrating a sonar system with an auxiliary array of magnetic sensors can improve the overall effectiveness of the intruder detection system. One of the major problems that arise from the use of magnetic systems is the interpretation of the magnetic signals coming from the sensors. In this paper a machine learning approach is explored for the detection of divers or, in general, of underwater magnetic sources that should ultimately support an automatic detection system. Currently this task requires a human online monitoring or an offline signal processing procedure. The proposed research, by windowing the sensed signals, uses Linear Support Vector Machines for classification, as tool for the detection problem. Preliminary empirical results show the viability of the method.

Keywords**:** underwater detection systems, port protection, magnetic signal processing, Support Vector Machine.

1. Introduction

For many years security has not been perceived by people as a necessity. Today, after some dramatic events, such as September 11 2001, security issue has become a serious concern not only for governments. As an immediate response to the biggest terrorist attack in modern history, the port security work has been concentrated on the shore side of business: inspections of containers with multiple sensors, gate crossing identifications, increased camera surveillance and security patrols, etc. In this scenario another problem, which previously was not being addressed, has become an issue of interest: the security of the areas from which a terrorist would be likely to launch an attack, the underwater. By this way, during the last five years, the research concerning underwater port protection has made some substantial achievements [1]-[7]. First of all the target of underwater intruder detection systems has been extended from a military one, such as an enemy nation navy submarine, to a terrorist one, such as a diver intruder. This produced a secondary effect concerning the up to date of the technology used to detect underwater sources: traditional sonar systems resulted to be insufficient to solve this task, bringing back importance to magnetic based systems [8]-[12]. The analysis and comparison of the performances of the two different approaches point out their peculiarities: acoustic arrays guarantee optimum volumetric control but lack in peripheral surveillance; vice versa magnetic subsystems achieve high peripheral security performances but partially fail in volumetric control. These considerations suggest the integration of both detection approaches into a dual system [7].

This integration guarantees a good effectiveness to the complete system: overlapping of the acoustic and magnetic subsystems supplies shadow areas avoidance and consequently prevents possible intrusions. Moreover in the zone of maximum uncertainty of each method the lack in performance of one approach is counterbalanced by the co-occurring presence of the other cooperating subsystem. While acoustic systems today are a commercial reality, magnetic underwater surveillance is still an open research field.

These premises lead to the demand of proper tools able to analyze the magnetic subsystem output. Beside classical analysis techniques [1]-[4] the purpose of this paper is introducing a machine learning tool, Support Vector Machine for classification, as a possible approach to automate the detection of diver intrusion patterns on the supplied data [13]. In particular, machine learning techniques have been already successfully used when coping with sonar signals [14]; here the purpose is showing that an analogous approach can be also carried when dealing with magnetic signals. Section 2 introduces the magnetic subsystem architecture while Section 3 exposes SVM theory, data extraction and experimental results.

2. The "MACmag" Magnetic Subsystem

Nowadays magnetic sensors have extremely high sensitivities and are able, in theory, to detect signals generated by human divers. This capability is strongly compromised in practice by the spectral content of the Earth's magnetic field in high noise environments, such as port areas, characterized by an extremely wide band and high amplitude components, which often hide the target signal. Given M spectral components of the magnetic field, if we call E_i the energy associated with the i-th component, the information content Q is given by [15], [16]:

$$Q = \sum_{i=1}^{M} E_i \tag{1}$$

Whereas the information capacity C_i, that is the capacity associate to the i-th elementary spectral component with its physical generator, is given by the ratio between the energy E_i and the total energy in which it is contained:

$$C_i = \frac{E_i}{Q} \tag{2}$$

The range of value of C_i is between 1 (monochromatic signal) and 0 (white noise or insufficient target signal amplitude):

$$\lim_{Q \to E_i} C_i = 1 \quad \lim_{Q \to \infty} C_i = 0 \quad \lim_{E_i \to 0} C_i = 0 \tag{3}$$

Considering the geomagnetic field composed by several magnetic signals produced by numerous sources of different type such as natural and artificial, internal and external to the Earth the effectiveness of port protection magnetic techniques identifies the magnetic security system capability to extract the target magnetic signal from all the superimposed signals which form the Earth magnetic field. Therefore the system capability depends on the very low Signal Noise ratio (S/N). This typical metrological problem may be critical to the effectiveness of the magnetic technique in the case of very low signal (i.e. swimmers or divers) in particular in high noise environmental conditions such as in a port scenario. The classic geophysical approach is studying and classifying the natural components of the geomagnetic field and therefore removing them trying to extract the target signal (in the magnetic environmental noise frequency band) using various numerical techniques. The magnetic technique upon which is based this paper is the so called High Definition Underwater Geomagnetism (HDUG), which consists in measuring the geomagnetic field far from the security barrier (reference sensor) and using the obtained magnetic graph for filtering the magnetic graphs coming from the magnetometers' array (sentinel sensors). If a target signal is present in one (or more) guard device's graph, the filtering process will extract the target signal otherwise the filtering process will get no information. A critical parameter of this technique is the position of the reference magnetometer: it has to be deployed close to the magnetometers network in order to get a coherent measurement of the geomagnetic environmental field through all the array's sensors (space coherence of the observatory) but at the same time far from guard magnetic sensors in order to not being interfered by the magnetic target signal. This critical distance depends on the difference in the "space stability" of the geomagnetic environmental field components and magnetic signal of target. In general, shorter the magnetic target signal and the geomagnetic time variations signal (and noise) are, higher the frequency of the magnetic signal is.

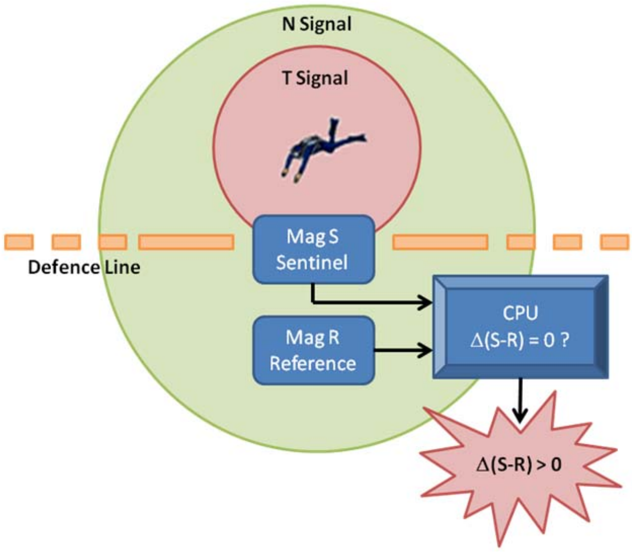

Figure 1. Structure of the sub-elementary cell of the magnetic system

Given two magnetometers, one as sentinel and the other as reference, to protect a critical area, in space coherence each other, one indicates with N the noise measured by both the magnetometers. By T is indicated the target signal acquired only by the sentinel magnetometer. As shown in [3], [4] it can be stated that the sentinel listen to N+T and the reference measures the environmental noise N (Fig. 1). This configuration can be obtained using two different architectures (Fig. 2 **A**, **B**) of the magnetic subsystem: the first is based on a sensor array and another external device used to obtain noise reference values (so that all the instruments in the array operate only as sentinel) and is called RIMAN-type network (Referred Integrated MAgnetic Network); the second employs the magnetic field acquired from the previous or next sensor in the array as noise reference (so that each instrument in the array operates both as sentinel and as reference) and is known as SIMAN-type network (Self-referred Integrated MAgnetic Network) [5], [7].

The RIMAN system consists of a magnetometers array system and an identical stand-alone magnetometer (referring node) deployed within the protected area.

The zero-level condition is obtained through the comparison of the signal measured by each of the array's magnetometers with the signal measured by the referring magnetometer. If the protected area is confined one can assume the total background noise constant and therefore the difference between each array's sensor and the referring one is around zero. The zero-level condition can be altered only in presence of a target approaching one or two (in case of middle-crossing) sensors of the array.

Signal processing of the RIMAN system is accurate and the risk of numeric alteration of the registered rough signal is very low. A standard data-logger system has to measure the signals coming from each of the array's magnetometers and respectively compare to the reference signal. The comparison functions ΔF10, ΔF20, …., ΔFN0 are subsequently compared to the reference level 0 and then only the non-zero differential signal is taken. It means that the target is crossing a specific nodal magnetometer. For

example, if the target is forcing the barrier between nodes 3 and 4, the only differential non-zero functions are ΔF30 and ΔF40 which will indicate the target's position. A quantitative analysis of the differential signals can also show the target's relative position to the two nodes. If the protected area is too wide to allow a stability condition of the total background noise, the RIMAN system can be divided in more subsystems, each of one using an intermediate reference node, which have to respect the stability condition among them. The intermediate reference nodes have finally to be related to a common single reference node.
In the SIMAN system all the array's magnetometers are used to obtain the zero-level condition. The control unit has to check in sequence the zero-level condition between each pair of magnetometers and signal any non-zero differential function. Signal processing in the SIMAN system gives very good accuracy, too. The only issue is related on the ambiguity in case the target crosses a pair of magnetometers at the same distance from both. Such ambiguity can be solved through the evaluation of the differential functions between the adjacent nodes. The drawback is that a SIMAN system requires a continuous second-order check at all the nodes. The advantage of using a SIMAN system is the possibility to cover an unlimited area. The stability condition is requested only for each pair of the array's magnetometers.
The system employed in the present work consists of two magnetometers in a SIMAN configuration. However, this configuration does not represent a full operational unit of the SIMAN network; a diver crossing halfway between the two sentinel magnetometers induces an analogous signal in both the devices and, consequently, this produces the target signal removal if target and reference signal are subtracted. Therefore, a full operational unit needs a third magnetometer which allows a comparison Δ(1,2), between the first pair of sensors, and Δ(1,3), between the second pair, such that the removal of the target can occur for at most one pair only (see Fig. 3) but not for the whole system.
Nevertheless the experimental configuration employed, including the two magnetometers, is clearly suitable for experimental validation of the magnetic system, with the exclusion of target crossings halfway between the two sensors. The magnetic signal used in ours experiments has been grabbed in this way from the sentinel and reference sensors in noisy environmental conditions and considering a civil diver as target. The eventual effectiveness of this architecture in detecting divers lies in this reference-target technique as exposed in [6]. The exigency of an automated detection system leads to the following explorative machine learning based analysis.

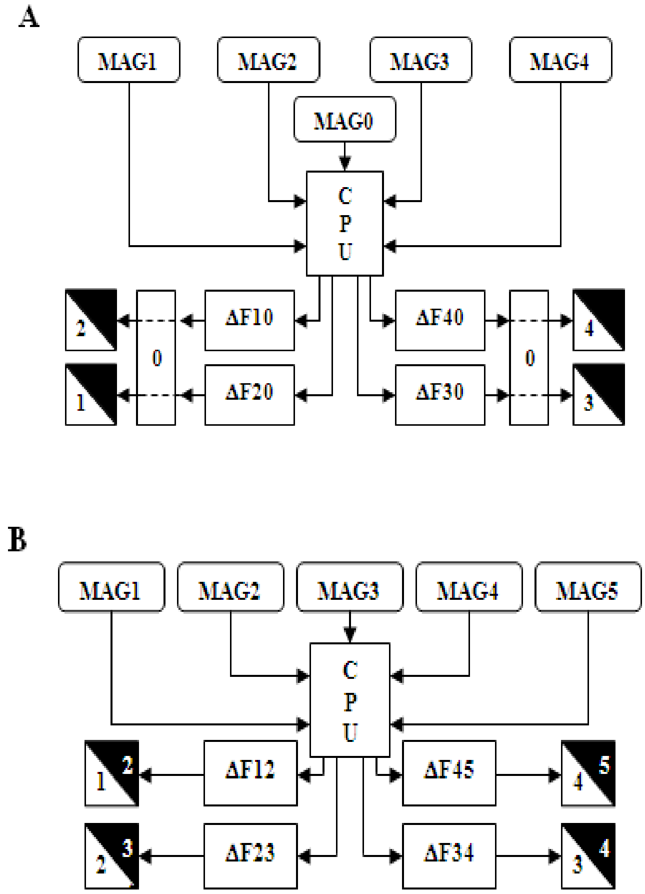

Figure 2. A) Scheme of Referred Integrated Magnetometers Array Network . **B**) Scheme of Self-referred Integrated Magnetometers Array Networks

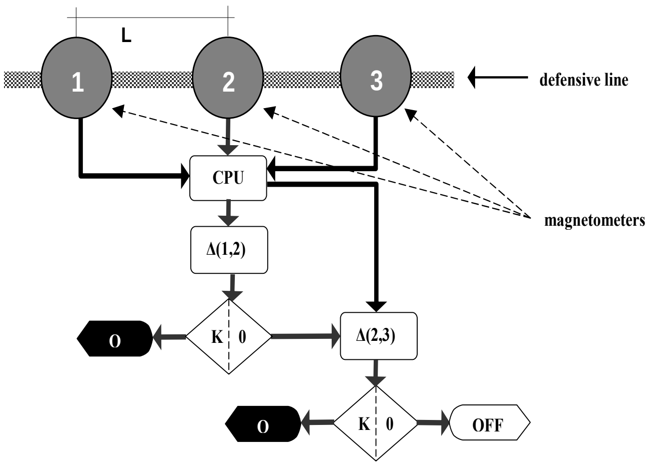

Figure 3. Operative structure of the elementary cell of the MAC mag subsystem

3. Support Vector Machines for Classification

Support Vector Machines (SVM) constitutes a robust and well known classification algorithm [17]. The good classification performance of SVMs is due to the concept of margin maximization, whose roots are deeply connected with Statistical Learning Theory [17].

As usual in learning machines, SVM has a learning phase and a prediction phase. In the learning stage the machine sees the training patterns and learns a rule (a hyper-plane) able to separate data in two groups according to data labelling. Conversely in the forward (prediction) phase the machine is asked to predict labels of new and unseen patterns.
From the formal point of view the following notation will be used:

- n_p is the number of patterns used as training set
- $\mathbf{X}$ is the training set
- $\mathbf{x} \in R^{n_i}$ is a pattern belonging to $\mathbf{X}$ where n_i is the data dimensionality
- $f(\mathbf{x}) = sign(\mathbf{wx} + b)$ is the prediction function based on the hyperplane defined by the normal $\mathbf{w}$ and the bias b
- $\mathbf{y}$ is the vector of labels of the training set, with $\mathbf{y} \in \{-1,1\}$

Given these definitions the cost function to be minimized for obtaining optimal $\mathbf{w}$ and b is:

$$C \sum_{i=1}^{np} (1 - y_i(\mathbf{wx} + b))_+ + \frac{1}{2}\|\mathbf{w}\|^2 \qquad (4)$$

Where the positive constant C controls the tradeoff between data fitting (the first term) and regularization (the second term that represents margin maximization), and where $(k)_+$ indicates $\max(0,k)$.

Problem (4) can be solved via quadratic optimization algorithms; despite this fact, problem (4) is usually solved using its Lagrange dual formulation. The dual formulation makes possible to use non-linear mapping functions called kernel functions [17] that lead to non linear separating surfaces (see Fig. 4). This operation is possible observing that the only operations in which data are directly involved are dot products.

Calling $K(\mathbf{x}_l, \mathbf{x}_m)$ the kernel dot product between $\mathbf{x}_l$ and $\mathbf{x}_m$ it can be shown [17] that the dual problem of (4) is:

$$\min_{\alpha} \left\{ \frac{1}{2} \sum_{l,j=1}^{np} \alpha_l \alpha_m y_l y_m K(\mathbf{x}_l, \mathbf{x}_m) - \sum_{l=1}^{np} \alpha_l \right\} \qquad (5)$$

$$\text{subject to: } \begin{cases} 0 \le \alpha_l \le C, \forall l \\ \sum_{l=1}^{np} y_l \alpha_l = 0 \end{cases}$$

Where vector $\boldsymbol{\alpha}$ is of length n_p and represents the set of dual variables.

In order to compute the global minimum of (5) one has to fulfil the Karesh Kuhn Tucker conditions:

$$\begin{aligned} \mathbf{w} = \sum_{i=1}^{np} \alpha_i y_i \mathbf{x}_i, \sum_{i=1}^{np} \alpha_i y_i &= 0 \\ C - \alpha_i - \mu_i &= 0 \\ y_i(<\mathbf{x}_i, \mathbf{w}> + b) - 1 + \xi_i &\ge 0 \\ \xi_i \ge 0, \alpha_i \ge 0, \mu_i &\ge 0 \\ \alpha_i \{ y_i(<\mathbf{x}_i, \mathbf{w}> + b) - 1 + \xi_i \} &= 0 \\ \mu_i \xi_i &= 0 \end{aligned} \qquad (6)$$

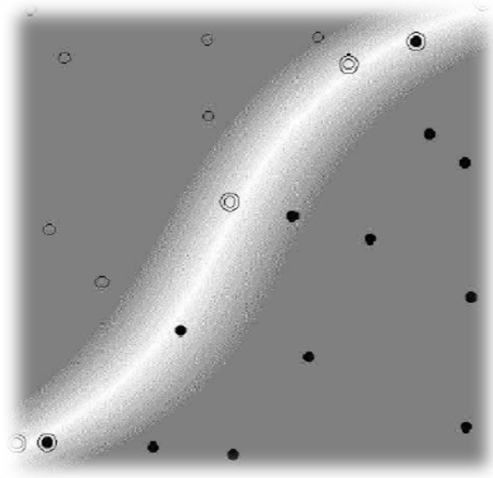

Figure 4. Non linear separating surface obtained by SVM using a non linear kernel function

Where $<\mathbf{x}_i, \mathbf{w}>$ denotes the dot product, ξ_i are slack variables and μ_i are Lagrange multipliers introduced to enforce $\xi_i \ge 0$. To fulfil (6) fast optimization techniques has been developed [18]. One of these techniques, called Sequential Minimal Optimization [19], is the one that will be used for the following experimental section.

Once (5) has been optimized, as a final step, one has an efficient way to compute the bias b [19].

Finally, provided $\boldsymbol{\alpha}$ and b the non linear prediction function can be written as:

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{np} \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b \right) \qquad (7)$$

It can be shown that the cost function in (4) leads to a sparse vector of coefficients $\boldsymbol{\alpha}$, i.e. several entries of $\boldsymbol{\alpha}$ are null; in turn this makes computation (7) less expensive.

When, as in this case, a linear kernel is used, (7), becomes:

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{np} \alpha_i y_i < \mathbf{x}, \mathbf{x}_i > + b \right) \qquad (8)$$

and represents a hyper-plane separating surface as per Fig. 5. Sparseness of alphas coefficients and the involved scalar product make (7) very appealing for an embedded device-based implementation: in order to compute (7) the computational primitives needed are, essentially, multiply and add units (MAC units); in this regard Digital Signal Processors perfectly suit this issue by their architectural structures. For these reasons a SVM model seems a possible feasible choice for such a task in view of an embedded electronics implementation.

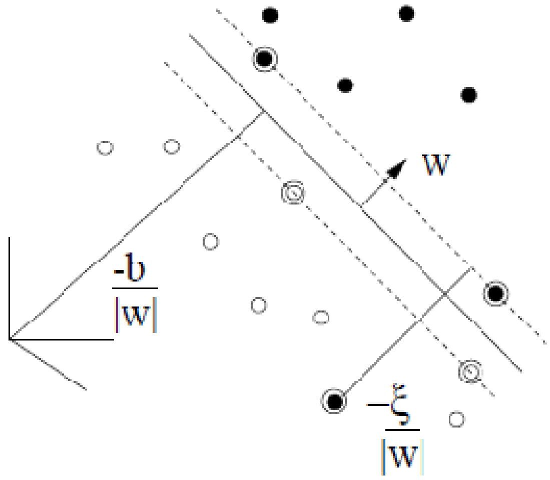

Figure 5. Linear separating surface with evidenced slack variables, bias and normal vector **w**

Figure 6. The Gulf of La Spezia, Italy (Image from Google Earth)

4. Experimental Results

The test area of the experiment was the Duca degli Abruzzi basin sited in the NW corner of La Spezia Gulf, Italy (see Fig. 6). This port environment is characterized by high electromagnetic noise. The critical area to be protected is represented by the section delimitated by the green line and the cost line (Fig. 7). The only way to enter into this zone is an access channel (into the protection's barrier) with a length of nearly130 [m] and a maximum water depth of about 11.50 [m] .

Fig. 7 and 8 show the critical zone to be protected (Fig. 7) and the extern zone (Fig. 8), separated by a black dashed line. Moreover Fig. 8 highlights the morphological features of the entrance way seafloor: the central sector is characterized by an approximately constant depth, the NE sector is characterized by an intense vertical positive gradient of depth, while the SW sector is characterized by a lower vertical positive gradient of depth. The vertical section's thickness of the passage, protected by the magnetic system, is an instrumental feature: in fact, it depends on the depth at which the sensors have been displaced. The magnetic system was placed in the basin entrance and was composed by two different magnetometers, one used as sentinel and the other as reference. The data were grabbed using a desktop linked to the two sensors with two underwater cables. All the records were stored in text files.

Starting from this conditions the first addressed step is the definition of a suitable dataset for SVM based classification.

Processed data refer to the problem of detecting the presence of a diver (class +1) or its absence (class -1).

Two quantities must be defined: the vector data **x** and its corresponding label *y*. The vector **x** can be created by windowing the signals coming from the magnetic subsystem: in particular given the original signal of length *m*, for each sample a window of width *l* is grabbed.

This means that the total number of windows (superposition of windows is allowed) is *m-l*. Because the signals coming from the subsystem are two (reference ambient signal and target detection signal), for each produced window the final pattern is built up by the concatenation of the two windows derived from the two signals.

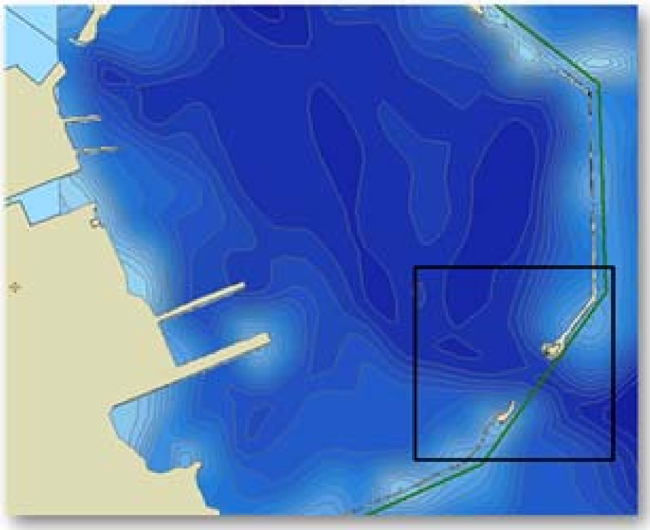

Figure 7. The Duca degli Abruzzi basin

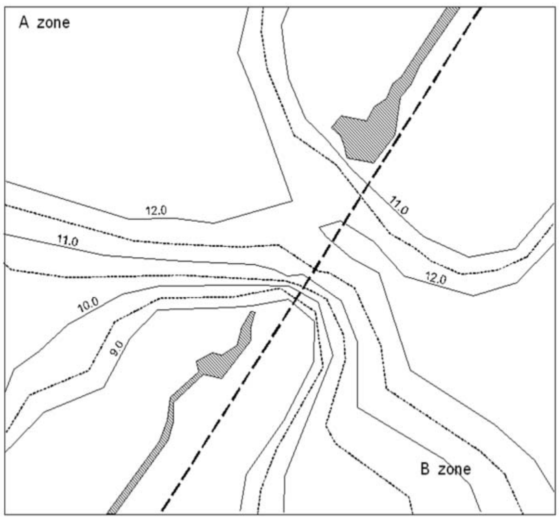

Figure 8. Bathymetric map of the observed area entrance

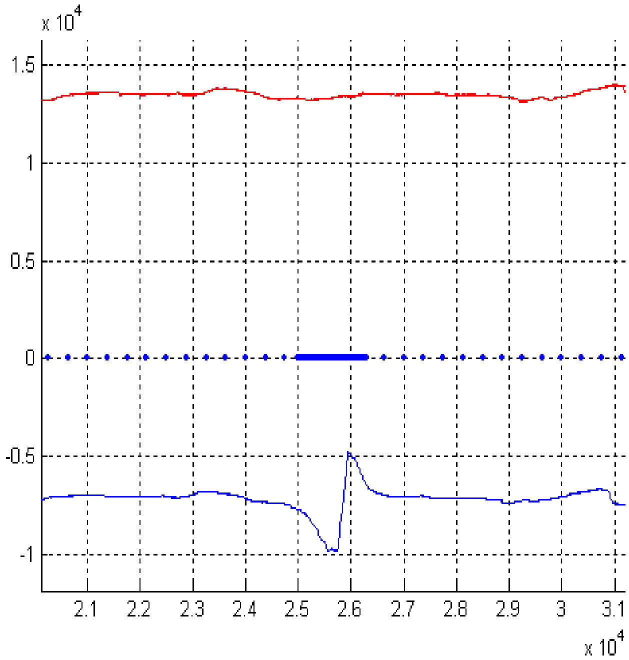

Figure 9. The upper signal is the reference signal; the lower signal is the target signal. Dotted line in the middle represents the windowing density

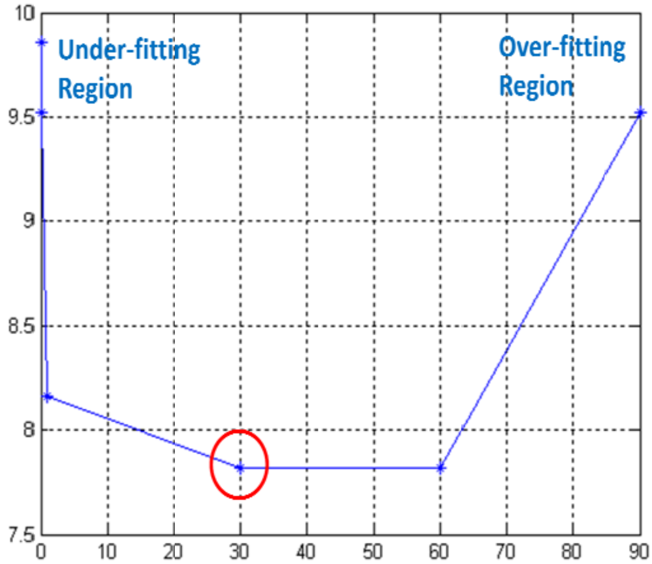

Figure 10. Model Selection curve: x axis are C values, y axis are percentage error values

The meaning of this concatenation of signals is showing to the machine contemporaneously the detection signal and the underlying environmental noise. In this way noise is not pre-filtered by a filtering system whose cut frequency choice is in general critical. For these reasons, and for the sake of simplicity, it is sufficient to work on time and not in frequency. This translates in having *m-l* patterns **x** each of size 2*l*. Using *l=100* the number of produced patterns is considerable; for this reason a random sub-sampling technique has been employed. The red line in Fig. 9 (upper line) shows an example of magnetic signal grabbed by the sentinel magnetometers while blue line (lower line) shows an example of magnetic signal acquired by the sentinel device. The sentinel signal highlights the presence of a magnetic target in the central region (magnetic dipole) crossing the instrument axis. The central dotted line represents the sub-sampling frequency. To obtain a meaningful dataset the sections of the signal which are characterized by an intrusion have been more densely windowed than the sections in which no intrusion occurs (see Fig. 9, units are classified data). All data were normalized for each attribute in the domain [-1,+1]. The experimental session was carried by using a SVM with standard linear kernel [17] and SMO [19] optimizer. In particular the accuracy on the optimality conditions was set to 1e-3, a typical value for SVM training convergence (Karesh Kuhn Tucker conditions [17], [19]). The model was selected according to the *C* regularization constant (as per (**4**)) that led to the lowest test set error. Table 1 summarizes the statistics of training and test data after applying the above mentioned sub-sampling technique.

Figure 10 depicts the obtained curve for the *C* values {0.01, 0.1, 1, 30, 60, 90}; its shape is in accordance with theory [17], showing underfitting regions (small *C* values) and overfitting regions (big *C* values).

Dataset	**Class +1**	**Class -1**
Training Set	142	145
Test Set	144	150

Table 1. Dataset overview.

Predicted Value	**Actual Value**	
	Positive	Negative
Positive	98.70%	1.30%
Negative	14.60%	85.40%

Table 2. Confusion matrix.

The best performances are obtained in the central region with *C = 30* and *C = 60*; for both this C values an error of about 7.82% occurs. Recalling that an underfitting behaviour is usually preferable to an overfitting one [17], the final selected parameter *C* was set to *C = 30.* The confusion matrix obtained in the best case is shown in table 2. The matrix shows the false negative (fn) rate (1.30%) and the false positive (fp) rate (14.60%). While the fn score is contained the fp score should be improved.

Considering that the current online detection system is human based or offline, the obtained results are quite promising mostly with the perspective of further improvements achievable by employing non linear kernel functions and data pre-processing techniques.

5. Conclusions

In the field of detecting fleeting underwater cinematic sources (i.e. malicious divers) the performances of detection systems based on a single sensor class (i.e. acoustic or electromagnetic systems) often results to have low confidence. For example, high performance of acoustic systems in the volumetric control is strongly reduced to effectiveness nearly zero in proximity of docks and seafloor, in particular if sea bottom is morphologically irregular or if there is a wreck on the sea floor. All this objects behave like acoustic reflectors that become active also in calm sea condition. On the contrary, auto-referred magnetic systems, based on the geometric concept of spatial stability noise-target, supply excellent performances in proximity of the sea bottom, also in case of irregular morphology, but its effectiveness decreases with the increase of the distance from the sentinel sensors. So, the acoustic subsystem is a typical volumetric observer, while the magnetic system is a typical peripheral observer. The integration between the two subsystems into a dual observation magnetic-acoustic system allows a high confidential covering barrier of the water section to be controlled, preserving the best features of the two single approaches.

Focusing the attention on the magnetic component, the current preliminary research showed that a Support Vector Machine for classification can be a feasible model for classification of underwater magnetic signals. A first experimentation with a linear kernel gave encouraging results about the achievable accuracy levels reachable with this approach; to get an on-field implementation, global accuracy and false negative rate must be further improved, moreover other methods and a sensor-failure detection policy should be studied. Future works will deal with the optimal windows size, a deep SVM-based model selection, i.e. using also kernel spaces, and other supervised and unsupervised classifiers (i.e. Circular Back-Propagation CBP, unsupervised clustering, etc…). Moreover other pre-processing techniques can be considered to make easier the classification task reducing the noise component of the grabbed signals.

Acknowledgment

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Author Biographies

Davide Leoncini was born in Genoa, Italy - 05 November 1983. He obtained the “Laurea” degree summa cum laude in Electronic Engineering in 2007 from Genoa University, Italy. Since 2008 he is pursuing a PhD, supported by a grant of NATO Undersea Research Center (NURC), in Electronic Engineering and Computer Science on embedded systems for intelligent, nonlinear signal processing. His main research areas include optimization of signal-processing algorithms for embedded systems and development of electronic systems, based on geomagnetic field, in underwater port protection scenario. He co-operates with the National Institute of Geophysics and Volcanology (INGV), the Italian Navy and WASS Company in the field of underwater magnetic systems for port protection.

Sergio Decherchi (born Genoa, Italy, 1983) obtained the “Laurea” degree summa cum laude in Electronic Engineering in 2007 from Genoa University, Italy. Since 2005 he started collaborating with the Department of Biophysical and Electronics Engineering of Genoa University, where he is pursuing a PhD in Electronic Engineering and Computer Science on Machine Learning. His main research areas include: theoretical aspects of Machine Learning, large scale learning algorithms development, semi-supervised learning, dedicated hardware for learning machines and Text Mining.

Osvaldo Faggioni was born in La Spezia, Italy - 22 August 1954. Patent of Ship Master, State Nautical College of La Spezia, Italy, 1972; “Laurea” Degree in Geological Science - Geophysical Course of Study, University of Genoa, Italy, 1977; PhD in Geophysics, University of Genoa, Italy, 1986. Main fields of his current study: metrology and numerical analysis of gravity and magnetic earth fields for man-made underwater magnetic microsources detection and forecasting of hydro-barometric sea level variations in harbours and coastal Newtonian districts. Chairman of the Defence Geophysics Group.

Paolo Gastaldo obtained the “Laurea” degree in Electronic Engineering and a PhD in Space Sciences and Engineering (2004), both from Genoa University, Italy. Since 2004 he is with the Department of Biophysical and Electronics Engineering of Genoa University, where he is the recipient of a research grant on Intelligent Systems for Visual Quality Estimation sponsored by Philips Research Labs – Eindhoven (NL). His main research area include innovative systems for visual signal understanding, neural network-based methods for nonlinear information processing, and DSP-based architectures for advanced signal interpretation, such as intelligent object tracking for video surveillance and cryptography.

Maurizio Soldani obtained the “Laurea” degree in Electronic Engineering from the University of Genoa, Italy. His current main research area is the development of signal-processing algorithms to analyze magnetic and gravity earth fields for underwater port protection and to forecast hydro-barometric sea level variations in harbours; he co-operates with the University of Genoa, the Italian Navy and WASS Company to develop underwater magnetic systems for port protection.

Rodolfo Zunino (born Genoa, Italy, 1961) obtained the “Laurea” degree cum laude in Electronic Engineering from Genoa University in 1985. From 1986 to 1995 he was a research consultant with the Department of Biophysical and Electronic Engineering (DIBE) of Genoa University. He is currently with DIBE as an Associate Professor, teaching Electronics for Embedded Systems and Electronics for Security. His main scientific interests include intelligent systems for Computer Security, network security and Critical Infrastructure Protection, embedded electronic systems for neural networks, efficient models for data representation and learning, massive-scale text-mining and text-clustering methods, and advanced techniques for multimedia data processing. Rodolfo Zunino coauthored more than 170 scientific papers in International Journals and Conferences; he has been the Co-Chairman of the two Editions of the International Workshop on Computational Intelligence for Security in Information Systems (CISIS’08 and CISIS’09). Since 2001 he is contributing as Associate Editor of the IEEE Transactions on Neural Networks, and has participated in the Scientific Committees of several International Events (ICANN'02, ICANN'09, IWPAAMS2004, IWPAAMS2005, Applied Computing 2006). Rodolfo Zunino is a Senior Member of IEEE (CIS – Computational Intelligence Society).